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Separating the Effects of Asymmetric Incentives and Inefficient Use of Information on Financial Analysts' Consensus Earnings Forecast Errors

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Abstract:

Prior research on financial analysts' consensus earnings forecast errors has tended to explore either incentives-based or inefficient information use-based explanations for the properties of the analysts' forecast errors. This has limited our understanding of financial analysts' expectation formation process as incentives and cognitive biases are likely to simultaneously affect the properties of the analysts' consensus forecast errors. Our main contribution is in separating these two effects. In particular, using consensus quarterly earnings forecast data, we document that analysts have asymmetric loss function and that they do not fully use information about past earnings and forecast errors in minimizing their expected loss.

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Introduction

Financial analysts are an important information intermediary whose forecasts influence market's expectations and are often used as a proxy for the unobservable market's expectations. Thus, many studies examine the properties of analysts' forecasts to draw inferences about analyst incentives and the extent to which analysts use information efficiently. Inferences about analysts' incentives are typically based on an examination of mean or median forecast errors. Inferences about information use on the other hand are based on OLS or LAD regressions of forecast errors on publicly available information.

These approaches have several important limitations. First, the mean and the median forecast errors are likely to be affected by how analysts use information, which results in ambiguous inferences about incentives. Second, inferences about how analysts use information based on OLS or LAD regressions in turn depend on the assumption that analysts have a symmetric quadratic or a symmetric linear loss function. If this assumption is empirically invalid, then we can wrongly reject or fail to reject the null hypothesis that analysts use information efficiently (Ellliott et al., 2004a, 2004b).

We attempt to make inferences about incentives and information use less ambiguous by analyzing forecast data with the help of a simple model of forecasting behavior. We view this model mainly as a useful tool to separate incentives from information use rather than as a true depiction of analyst incentives.

We represent financial analysts' incentives by either a quadratic or a linear loss function with a single unknown parameter, α, capturing the amount of asymmetry in the loss function.[1]

[1] For brevity, we will often say that we assume a quadratic or a linear loss function. What we always mean is that we assume a quadratic or a linear loss function with an unknown single parameter capturing the amount of asymmetry in the loss function. The quadratic loss function differs from the linear loss function only in that costs are attached to

For example, an α of 0.75 (0.25) means that the cost of a positive forecast error is three times as high (low) as the cost of a negative forecast error, or that analysts have incentives to issue optimistic (pessimistic) forecasts. A parameter of 0.5 represents the case of symmetry. In addition to being simple, this functional form nests the traditional symmetric linear and quadratic loss functions (Basu and Markov, 2004).

An optimizing forecaster would use all available information to issue a forecast that would minimize her expected loss. We use the first-order conditions from this minimization problem to estimate the unknown loss function parameter that is most consistent with the data. The loss function parameter is identified even if analysts do not use information efficiently, which allows us to make inferences about incentives without assuming efficient information use.

Our measure of efficient information use (forecast optimality) is Hansen's J-statistic, which checks how well the first-order conditions are satisfied.[2] In contrast to prior studies' measures of information use, our measure is valid even if the loss function is not symmetric.

We recover the asymmetry parameter of the analysts' loss function from quarterly earnings forecasts data and assess the extent to which analysts use past forecasts errors and past earnings in minimizing their expected loss. Under the linear specification of the loss function, we find that positive forecast errors are less costly than negative forecast errors. In fact, in recent years, the cost of positive forecast errors is about half as high as the cost of negative forecast errors. We simultaneously document inefficient use of information by analysts under this

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squared forecast errors rather than absolute forecast errors. Unlike prior studies (Gu and Wu, 2003; Basu and Markov, 2004), we make no argument about whether quadratic or linear specification is more reasonable. Readers who favor one specification are free to disregard evidence obtained under the other.

[2] The econometric approach used in this paper is developed and applied first to macroeconomic forecasts by Ellliott et al. (2004a, 2004b). It is described in Section 2. The basic idea of recovering a parameter from the data that is most consistent with optimizing behavior and assessing the extent to which optimality restrictions are satisfied in the data appears first in Hansen and Singleton's seminal (1982) study.

asymmetric loss function. In particular, we find that analysts do not fully use information in past forecast errors and past earnings in minimizing their expected loss.

In the quadratic specification, we also document the existence of asymmetric incentives. The asymmetry is reversed as we find that positive forecast errors are more costly than negative forecast errors. However, analysts display similar inefficient use of past forecast errors and past earnings information in minimizing their expected loss. The choice between linear and quadratic specification is important for making conclusions about analysts' incentives, but inconsequential for making conclusions about analysts' use of information.

We also examine whether analysts' incentives and use of information vary across investment firms and over time. We find no evidence that analysts employed by the ten premier investment firms that participated in the Global Settlement of 2003 (GS analysts) have more asymmetric incentives or use information less efficiently than other analysts (Non-GS analysts). If anything, the cost of negative forecast errors in the GS analysts' loss function tends to slightly exceed the cost of negative forecast errors in the non-GS analysts, and GS analysts tend to use information more efficiently than non-GS analysts. Our findings offer no support for the argument that the GS firms produced more optimistic research due to investment bankers' influence on financial analysts.

Following Kadan et al. (2004), we partition our sample period of 1985 to 2004 into *Pre-Reg FD* (1985-10/2000), *Reg FD-GS* (10/2000-12/2002), and *Post-GS* (04/2003-2004) periods. The objectives of Regulation FD (Reg FD) and the Global Settlement (GS) is to strengthen analysts' incentives to issue unbiased and accurate forecasts by weakening managers' (Reg FD) and investment bankers' (GS) influence on analysts. Thus, we expect to observe smaller loss function asymmetry, and perhaps better use of information by analysts in producing their earnings forecasts.

Under the linear loss function representation, the loss function asymmetry is most pronounced in the *Post-GS* period. The cost of positive forecast errors is about 1.5 times as low as the cost of negative forecast errors in the *Pre-Reg FD* (α of about 0.42), and about twice as low as the cost of negative forecast errors in the *Post-GS* period (α of about 0.3). Under the quadratic representation we find that the loss function asymmetry is most pronounced in the first period. The cost of positive forecast errors is about three times as high as the cost of negative forecast errors in the *Pre-Reg FD* period (α=0.75). In the *Post-GS* period, the cost of positive forecast errors is still higher, but some parameter values are as low as 0.57. In sum, in both specifications we document a downward trend in α, which can be attributed to stronger incentives to issue lower forecasts. In both specifications and in all time periods we tend to document the inefficient use of information. The test statistics in the *Post-GS* period, however, are consistently lower than those in the *Pre-Reg FD* period, which we interpret as more efficient use of information in that period.

Our empirical analysis has implications for both researchers and policy makers. First, what the data reveal about analyst incentives ultimately depends on the model of incentives. Our stylized model can be supplanted by richer specifications, grounded in institutional evidence about the consequences of making forecast errors or theoretical considerations about the optimality of a loss function (Lambert, 2004), to yield novel insights into analyst forecasting behavior. Second, designing effective policies to influence the properties of analyst forecasts requires some knowledge about the effects of incentives and information use. The general approach of recovering financial analysts' loss function from the data thus can significantly inform the public policy debate about financial analysts' alleged lack of incentives to issue unbiased forecast.

The rest of the paper is organized as follows. Section 2 describes our econometric method. Section 3 describes our sample. Empirical analysis is presented in Section 4, and Section 5 concludes the paper.

2. Econometric method

In this section, we provide a brief overview of our econometric method, which was developed by Elliot et al. (2004a, b) to estimate the parameter of a forecaster's loss function and the extent to which the forecaster is successful in minimizing her expected loss. The basic idea of recovering a parameter from the data that is most consistent with optimizing behavior and assessing the extent to which optimality restrictions are satisfied in the data appears first in Hansen and Singleton's seminal (1982) study.

2.1. Representation of analysts' objectives

The main features of the model are that larger forecast errors are more costly, and that the cost of a forecast error may depend on its sign. In particular, the consequences of making an inaccurate forecast are represented by the loss function

$$L(p,\alpha,\theta) \equiv \left[\alpha + (1-2\alpha)\cdot 1\left(A_{t+1} - f_{t+1}(\theta) < 0\right)\right]\cdot\left|A_{t+1} - f_{t+1}(\theta)\right|^{p}. \tag{1}$$

The second term, $\left|A_{t+1} - f_{t+1}(\theta)\right|^{p}$ is the analyst's forecast error defined as the difference between earnings, A_{t+1} and the earnings forecast, $f_{t+1}(\theta)$. The latter is a linear function of variables W_t

observed by the analyst at time *t*, $f_{t+1}(\theta) = \theta \cdot W_t$. Different values of θ represent different forecasting rules, which in turn result in different forecast errors. The first term in equation (1), $\left[\alpha + (1-2\alpha)\cdot 1\left(A_{t+1} - f_{t+1}(\theta) < 0\right)\right]$ makes the cost of a forecast error conditional on its sign. If α is equal to 0.5, then positive and negative forecast errors are equally costly. In fact, when α=0.50 and p=1, or 2, the loss function reduces to the familiar cases of a symmetric linear or a quadratic loss functions widely used in prior research on financial analysts. If α>0.5, however, then over-predictions are less costly to the analyst. In other words, the analyst has incentives to over-predict earnings. In conclusion, our ignorance about the analysts' objectives consists only of not knowing the value of the single parameter α, $\alpha \in (0,1)$.

2.2. The moment conditions

As an optimizing agent, the analyst chooses a forecasting rule $f_{t+1}(\theta) = \theta \cdot W_t$ to minimize her expected loss

$$\min_{\theta} E\left[L(p,\alpha,\theta)\right]. \tag{2}$$

If θ is chosen optimally, then the forecast errors must satisfy the first-order conditions

$$E\left[W_t \cdot \left(1\left(\varepsilon^*_{t+1} < 0\right) - \alpha\right) \cdot \left|\varepsilon^*_{t+1}\right|^{p-1}\right] = 0, \tag{3}$$

where $\varepsilon^*_{t+1} = A_{t+1} - \theta^* W_t$.[3] Having access only to a subset of the information available to the analyst at time *t*, which we denote as V_t, does not prevent us from estimating α. Since an optimizing analyst exploits any information available to her at time *t*, we can substitute V_t for W_t

[3] This is proposition 1 in Elliot et al. (2004a).

in the moment conditions and use the corresponding sample moments to back out the asymmetry parameter α.

2.3. Estimation

Incentives, as parameterized by a loss function with a single unknown parameter, place restrictions on how optimizing analysts use publicly available information, such as past forecast errors and past earnings changes. As long as we have more moment conditions than parameters to estimate, we are able to recover the asymmetry parameter without ad hoc rationalizing the forecasts. The reason for this is that the same α has to set two or more sample moments simultaneously to zero. Accordingly, our estimator of α minimizes a quadratic form

$$q = g_T(\alpha)' S g_T(\alpha) \tag{4}$$

where $g_T(\alpha)$ is the sample equivalent of equation (3), and S is a weighting matrix. Our weighting matrix is the inverse of the covariance matrix of the moment conditions, which minimizes the asymptotic variance of the GMM estimator. [4] In addition, we allow for heteroscedasticity and intra-quarter correlation.[5]

2.4. Test of forecast optimality and relation to prior studies on analysts' incentives and information use

We use the terms "forecast optimality" and "efficient information use" interchangeably. If the analyst's forecast minimizes her expected loss, then we say that the forecast is optimal under the assumed loss function, or that the analyst's forecast uses efficiently all publicly

[4] The weighting matrix determines the relative importance of setting a particular moment condition to zero when estimating α. For example, using the identity matrix amounts to treating all moment conditions the same way.
[5] We used Stata's **ivreg2** command and its options **cluster** and **robust** for that purpose.

available information. Statistically, the distance between the sample moments and zero for such a forecast will be very small. Hansen's J-statistic, which is equal to the minimized value of the quadratic form (equation (4)), measures how close to optimality the forecasts are, or alternatively, how well the first order conditions are satisfied. It follows a chi-square distribution with degrees of freedom equal to the difference between the number of moments and number of parameters estimated. Large values of the J-statistic result in a rejection of the null hypothesis of forecast optimality.

To appreciate the link between this test of optimality and prior tests of optimality under symmetric loss functions, we substitute a known α of 0.5 and p=2 into the moment conditions (equation 3), and obtain

$$E\left[W_t \cdot \varepsilon_{t+1}^*\right] = 0\,. \tag{5}$$

These moment conditions are the familiar optimality predictions under the symmetric loss function that the forecast errors are orthogonal to information known to the analyst. Researchers then examine whether they are satisfied by estimating the regression model

$$\varepsilon_{t+1}^* = \beta_o + \beta_1 V_t + \varpi_{t+1} \tag{6}$$

and testing the set of restrictions: β_0=0 and β_1=0. However, if the loss function is not symmetric, then we can incorrectly reject or fail to reject the null hypothesis of forecast optimality.[6]

At first glance, it may appear that our approach rationalizes analyst forecasts by searching over loss functions. Lambert (2004) points out the dangers from undisciplined search for loss functions that would make the forecasts appear rational: "It is probably the case that for many distributions of analyst forecast errors, we could find some loss function that made them appear

[6] The importance of correctly specifying analysts' loss function for conducting inferences about earnings forecast optimality is emphasized in Gu and Wu (2003), Abarbanell and Lehavy (2003), Cohen and Lys (2003), Basu and Markov (2004), and Lambert (2004).

rational. While changing the weights applied to errors of different size or different signs may make them appear "rational", this does not change the fact that the errors are there." (p. 220). The gist of our approach is, however, not in proposing alternative loss functions, but in generalizing the existing ones. The existing loss functions assume a specific parameter value, 0.5, that is neither supported by empirical evidence, nor derived from theory. We estimate the asymmetry parameter based on a set of restrictions derived under the null hypothesis of forecast optimality (efficient information use). The only disadvantage in not enforcing symmetry is that it reduces the power of our tests to document inefficient information use, if the loss function is truly symmetric. Given that we almost always reject the null of efficient information (results are discussed in section 4), low power does not appear to be a concern.

Equation (6) is also the basis for documenting the existence of asymmetric incentives. Comparing mean (median) forecast errors of affiliated and unaffiliated analysts is equivalent to estimating an OLS (LAD) regression of forecast errors on an indicator variable equal to one, if the analyst is affiliated, and zero otherwise. More generally, if the variable V_t^i (the superscript *i* stands for incentives) is viewed as being only a proxy for incentives, then a non-zero coefficient on V_t^i can be interpreted as evidence that incentives are not constant. There are several disadvantages of this approach. First, the documented variation in mean or median forecast errors can be driven by variation in how analysts use information. Second, it seems contradictory to first assume that analysts are trying to minimize their mean squared error, then test whether a difference in mean squared errors exists, and finally attribute the difference in mean squared error to difference in incentives. Since we expect incentives to be asymmetric, we can suitably parameterize incentives, and then directly estimate the asymmetry parameter.

Chen and Jiang (2004) use a version of equation (6) to explore rational and behavioral explanations for why individual analysts' forecast deviations from the consensus predict individual analysts' earnings forecast error. There are two major differences between their study and ours. First, since Chen and Jiang (2004) use equation (6), they only document that individual analysts' incentives are not symmetric without quantifying the amount of asymmetry. More importantly, Chen and Jiang's (2004) evidence speaks to why individual analysts' earnings forecasts deviate from the consensus, while our analysis focuses on the extent to which the consensus incorporates publicly available information that is useful for forecasting future earnings.

2.5. Variation in asymmetry parameter and forecast optimality

We estimate a loss function asymmetry parameter and conduct a test of forecast optimality across different investment firms and over different time periods. We provide our motivation next.

2.5.1. Across investment firms

In general, the loss function asymmetry stems from analysts' incentives to: (1) help investments bankers bring in revenues (Dugar and Nathan, 1995; Lin and McNichols, 1998), (2) retain privileged access to managers' inside information (Francis and Philbrick, 1993; Das et al., 1998; and Lim, 2001), (3) generate buy trades (Dorfman, 1991; Hayes, 1998; Irvine, 2000), and (4) appease investors long in the stock (Bradley et al., 2005). The Global Settlement of 2003 involves ten investment firms (GS firms, or GS analysts henceforth) with significant amount of investment banking operations: Bear, Stearns & Co. Inc., Credit Suisse First Boston LLC, Goldman, Sachs & Co., Lehman Brothers Inc., J.P. Morgan Securities Inc., Merrill Lynch, Pierce, Fenner & Smith, Incorporated, Morgan Stanley & Co. Incorporated, Citigroup Global Markets Inc. f/k/a Salomon Smith Barney Inc., UBS Warburg LLC, and U.S. Bancorp Piper Jaffray Inc. [7] The Global Settlement imposed stiff monetary penalties on these firms and required structural reforms of investment research that limit communications between investment bankers and research analysts, restrict analyst involvement in the IPO process, and forbid any investment bankers' input into analyst evaluation and compensation.[8]

Since only ten investment firms were the subject of the enforcement action, it is interesting to provide large sample evidence on whether analysts employed at GS firms had weaker incentives to issue unbiased and accurate research from analysts employed at non-GS firms. An alternative explanation for why these firms were chosen is that it is efficient to investigate and settle with the largest providers of investment research.

2.5.2. Over time

One of the objectives of Regulation Fair Disclosure (Reg FD), enacted in October 2000, is to eliminate the asymmetry in analysts' loss function that stems from analysts' reliance on managers for information. It bans the disclosure of private information to analysts, thereby making it harder for managers to punish/reward analysts by withholding/providing private information. Reg FD was followed by increased scrutiny of Wall Street research practices by the media and regulators. In the period between Reg FD and the Global Settlement, important events that shaped the regulatory environment were: the Securities Industries Association's publication

[7] Regulators participating in The Global Settlement are the SEC, NASD, NYSE, several state attorney generals, and the North American Securities Administrators Association.
[8] Information about the terms of settlement, court orders, and other general information is available online at http://www.sec.gov/spotlight/globalsettlement.htm.

of "Best Practices for Research" and the beginning of Spitzer's investigations in 2001; the proposal and approval by the SEC of amendments to NYSE's Rule 472 and NASD's Conduct Rule 2711[9], Spitzer's settlement with Merrill Lynch, the signing of Sarbanes-Oxley Act, additional rule proposals by NYSE and NASD, the proposal of Regulation AC by the SEC, two Congressional hearings, and the initial settlement between regulators and major investment banks in 2002; the approval of Regulation AC, the Global Settlement with major investment banks, and additional rule making by NYSE and NASD[10] in 2003 (see Skiles (2003) for more information). The new rules of NYSE and NASD on analysts' compensation, which are binding on all investment firms, similarly ban investment-banking input in analysts' compensation and require that compensation be based on the quality and accuracy of analyst' research. Thus, we expect to observe a general trend toward greater loss function symmetry, and more efficient use of information by all analysts. We conduct our analysis for three distinct time periods. *Pre-Reg FD* (1985 through September 2000) is the period before Reg FD became effective. *RegFD-GS* (October 2000 to December 2002) is the period after Reg FD became effective and before the terms of the Global Settlement were first announced. *Post-GS* (April 2003 to December 2004) is the period in which both Reg FD and the Global Settlement are effective.

3. Sample description

3.1. Variables

Our primary data come from the Institutional Brokers Estimate System (I/B/E/S) database. We use the I/B/E/S Detail Earnings Estimate History File which contains individual analysts' quarterly earnings forecasts for U.S. companies for the period from January 1985 to

[9] These rules are described in SEC Release 34-45908.
[10] The amendments to NASD Rule 2711 and NYSE Rule 472 are described in SEC Release 34-48252.

December 2004. We also use the I/B/E/S Detail History Broker Translation file, which provides translations of the BROKER and ANALYST codes in the Detail file to actual investment firm and analyst names (if available) to identify GS firms.

Our analysis uses consensus forecasts constructed from individual analysts' forecasts. There are several motivations for using consensus rather than individual analysts' earnings forecasts. First, there could be random variation in how analysts use information. By using the consensus forecast that likely averages out individual analysts' mistakes, we can better understand the incentives operating on financial analysts as a group, as well as the extent to which their forecasts incorporate available information. Second, our objective is to describe the common component of individual analysts' loss functions. This component could be induced by employment at the same investment firm, or by employment at investment firms that follow similar compensation policies, or are subject to the same regulations.

We denote the quarterly I/B/E/S earnings per share (EPS) for quarter $t+1$ as A_{t+1}, and the consensus forecast of A_{t+1} as F_t^{t+1}. The consensus is defined as the median of the first available individual analyst forecasts issued after the announcement of A_t. We exclude forecasts issued in the second half of the period between earnings announcements A_t and A_{t+1}. These forecasts are likely to be more efficient with respect to information available at time *t* simply because some of the information arriving during the quarter is likely to confirm what is known but ignored by analysts at time *t* (Soffer and Lys, 1999). The forecast error FE_t^{t+1} is defined as A_{t+1}- F_t^{t+1}, and $(A_t - A_{t-1})$ is the earnings change in the quarterly I/B/E/S EPS for the quarter t. All variables are scaled by the share price recorded for the earnings-announcement month of the quarter t-1 obtained from IBES to alleviate heteroscedasticity concerns and are winsorized at the 1% level on both tails to eliminate outliers.

In addition to constructing a consensus forecast that includes forecasts issued by all investment firm, *All firms consensus forecast*, we construct both a *GS consensus forecast* and a *non-GS consensus forecast*. The former (the latter) includes only forecasts issued by analysts employed at GS (non-GS) investment firms. Our motivation is to assess differences in loss function asymmetry and use of information between GS and non-GS firms.

As changes in the regulatory environment may change analysts' incentives and how they use information in producing their forecasts, we examine the properties of these different types of consensus forecasts for three distinct time periods: *Pre-Reg FD*, *Reg FD-GS*, and *Post-GS*. More details about the sample construction are provided in Appendix A.

3.2. Descriptive Statistics

Table 1 provides descriptive statistics on the sample. Panel A of Table 1 provides information about investment firm size as measured by number of analysts employed. We determine the number of analysts employed by a given investment firm in a given year based on the I/B/E/S Detail Earnings Estimate History File. We then average over calendar years and investment firms to calculate mean, median, standard deviation, and 25th and 75th quantiles of the distribution of number of analysts employed by GS firms and non-GS firms over the three time periods.

The mean number of analysts employed by a GS firm is about 65, 127, and 108 in the *Pre-Reg FD*, *Reg FD-GS*, and *Post-GS* periods. The corresponding statistics for a non-GS firm are 7, 12, and 9. Thus, the distribution of firm size appears to be highly skewed with the GS firms being the largest employers. From a regulator's perspective, it could be efficient to investigate and settle with the few investment firms that employ the largest number of analysts.

The drop in analyst employment from *Reg FD-GS* period to *Post-GS* period is perhaps due to the lower value from employing analysts induced by the ban on analyst participation in investment banking deals. At the same time, untabulated results show an increase in the number of non-GS firms from *Reg FD-GS* to *Post-GS* period. This could be in response to stronger demand for alternative sources of investment research due to perception of tainted research at the GS firms and new regulatory requirement that GS firms make available third party research to their customers.

Panel B provides descriptive statistics about the number of forecasts included in the All firms, GS and non-GS consensus forecasts over the three time periods. The mean number of forecasts included in the GS (non-GS) consensus forecasts in the *Pre-Reg FD*, *Reg FD-GS*, and *Post-GS* periods is about 2.4 (4), 3.2 (5.1), and 3.3 (6). In general, the greater the number of forecasts included in the consensus, the more likely that individual analyst mistakes average out. Whether the difference in number of forecasts included in the GS and non-GS consensus will translate into difference in consensus forecast optimality is an empirical question.

Panels C report descriptive statistics on the variables used in our statistical analysts; consensus forecasts, consensus forecast errors, actual EPS, and past earnings change (F_t^{t+1}, FE_t^{t+1}, A_{t+1} and $(A_t - A_{t-1})$). We document that mean forecast errors are consistently negative and median forecast errors are consistently positive. Both mean and median forecast errors exhibit an upward trend. Median (mean) forecast errors are 0, 0.0003, and 0.0005 (-0.0022, -0.0011, -0.0007) in the *Pre-Reg FD*, *Reg FD-GS*, and *Post-GS* periods.

The traditional approach to drawing conclusions about analysts' incentives is to hypothesize a difference in incentives, and then test for differences in mean or median forecast errors. Consider the evidence in Table 1 that median forecast errors for all firms is zero in the *Pre-Reg FD* period, 0.0003 in the *Reg FD-GS* period, and 0.0005 in the *Post-GS* period. The interpretation, based on the traditional approach, would be that analysts have stronger incentives to issue pessimistic forecasts in later periods. The limitations of this approach are obvious. First, incentives are not quantified as they are not formally modeled. More importantly, forecast errors are viewed as being informative only about incentives, but not about how analysts use information. In principle, a combination of asymmetric incentives and inefficient use of information can result in a zero median forecast error.

4.1 Empirical evidence on loss function asymmetry and analysts' use of information for quadratic and linear and linear specifications

4.1. Linear specification

Panels A, B, and C of Table 2 report the results from our estimations under the linear representation of the loss function for three separate time periods; Pre-*Reg FD*, *Reg FD-GS*, and *Post-Reg FD.* We report asymmetry parameter, α_l and J-statistic for *All firms, GS firms*, and *non-GS firms*. We use four different sets of instruments: vector of one; vector of one and past forecast errors; vector of one and past earnings changes; and vector of one, earnings at lag one and two, and a forecast of earnings at lag one. These information items are known to the analysts as our consensus incorporates only forecasts issued after the announcement of past quarter's earnings.

Before we discuss the evidence in Table 2, consider first the evidence in Panel C of Table 1 that median forecast errors for all firms are 0 in the *Pre-Reg FD* period, 0.0003 in the *Reg FD-GS* period, and 0.0005 in the *Post-GS* period. Using the traditional approach we concluded that analysts have stronger incentives to issue pessimistic forecasts in later periods. Our estimation with a single instrument improves over the traditional approach in that it provides an empirical measure of asymmetric incentives and of how they changed during the period. In particular, the cost of positive forecast error decreased from 0.41 in the *Pre-Reg FD* period to 0.30 in the *Post-GS* period (reported in the first row of Panels A and C, Table 2). This alternative approach, however, still assumes that the properties of the forecast error distribution are reflective only of analysts' incentives. If analysts do not use information efficiently, then it is possible that the true cost of a positive forecast error is different from our estimate of 0.41.

Our estimations that use more than one instrument overcome this limitation by effectively considering additional information that may have been used inefficiently and thus may account for our findings of α_l equal to 0.41. Our econometric approach selects a single parameter value that sets all sample moment conditions as close to zero as possible and then evaluates the distance between the moment conditions and zero. After adding past forecast errors as an additional instrument, in the period *Pre-Reg FD* we document a slightly higher α_l of 0.43, and that the distance between zero and the sample moment conditions is "too" large; for this case, the J-statistic is 53.21 (Panel A, Table 2). Any concern that relaxing the symmetry assumption may compromise our ability to detect inefficient use of information is not justified as we reject the null hypothesis of forecast optimality in the period *Pre-Reg FD*. Thus, we are able to document two distinct phenomena: (1) analysts have asymmetric loss function and (2) their forecasts do not incorporate all available information in minimizing their expected loss. In the rest of this section, we discuss our findings based on this approach; we use more than one instrument to simultaneously estimate the loss function parameter and test for forecast optimality.

In the *Pre-Reg FD* period, we document an α_1 of 0.42 while in the *Reg FD-GS* and *Post-GS* period we document an α_1 of 0.32 and 0.30 (reported in Panels A,B and C of Table 2). In other words, the cost of a positive forecast error is about 1.5 times as low as the cost of a negative forecast error, and more than twice as low as the cost of a negative forecast error in the *Reg FD-GS* and *Post-GS* periods. At the same time, we document a trend toward more efficient information use. The J-statistics are consistently lower in the *Post-GS* period than in the *Pre-Reg FD* period, and we do not always reject the null hypothesis of efficient information use. In conclusion, we document the co-existence of asymmetric incentives and inefficient information use.

We do not find significant differences in α_1 between GS and non-GS firms in any period. The maximum difference is observed in the *Post-GS* period when non-GS firms' α_1 exceeds that of GS firms' by 0.03 or 0.04 (Panel C, Table 2), depending on the instruments we use. However, we reject the hypothesis of equal loss functions most of the times. The documented higher cost of making positive forecast errors for analysts employed by non-GS firms suggests that they have stronger incentives to issue higher forecasts than analysts employed at GS firm.

In general, both GS and non-GS analysts fail to extract all information in past forecast errors and earnings to minimize their expected loss. The J-stat for GS analysts, however, tends to be lower than the J-stat for non-GS analysts, and in one case we fail to reject the null of efficient use of information by GS analysts while still rejecting the same null for non-GS analysts.

4.2. Quadratic specification

The evidence presented in Table 3 is generated under the assumption of quadratic loss function. As we discuss our results, we will contrast our conclusions about analysts' incentives and forecast optimality under alternative loss function assumptions. Until evidence to unambiguously validate one assumption is provided, it is worthwhile to study analysts' incentives and analysts' use of information under alternate assumptions.

In the quadratic specification, we find strong evidence that positive forecast errors are more costly than negative forecast errors. For example, the loss function asymmetry parameter, denoted as α_q, ranges between 0.70 and 0.78 in the *Pre-Reg FD* period, 0.58 and 0.69 in the *Reg FD-GS* period, and 0.58 and 0.75 in the *Post-GS* period (Panels A, B and C of Table 3). This contradicts our findings under the linear specification that α is less than 0.5 (Panels A, B and C, Table 2). The contradictory findings about α, or the relative costs of positive and negative forecast errors, echo the similarly contradictory findings about positive median forecast errors and negative mean forecast errors (Table 1, Panel C). Our findings on how analysts use information under the quadratic loss function, however, agree with our findings under the linear loss function. We reject the null hypothesis of forecast optimality in all time periods. Conclusions about how analysts use information do not appear to depend on how we specify the loss function.

Just like in the linear representation, we find evidence that GS analysts' loss function differs only slightly from that of non-GS analysts. Their cost of making positive forecast errors, while still greater than 0.5, is lower than that of non-GS analysts, which means that non-GS analysts have stronger incentives to issue optimistic forecasts. Furthermore, in the *Reg FD-GS* period and in the *Post-GS* period, we often fail to reject the null hypothesis of loss function symmetry for GS brokers, while we always reject the null hypothesis of symmetry for non-GS brokers. This evidence suggests that GS analysts' loss function is closer to being symmetric. At the same time, we caution our readers against concluding that regulators targeted the GS brokers only because of their large pockets and visibility. The issues of how much information investors had about GS and non-GS analysts' incentives and how much investors relied on analyst reports published by GS and non-GS analysts when making investment decisions, while undoubtedly important for formulating regulatory policies, are not addressed in this study.

The stylized facts emerging from our analysis are as follows. Financial analysts' loss function is asymmetric, and analysts do not fully use past earnings and forecast errors information to minimize their expected loss. In the linear specification, we find that positive forecast errors are less costly than negative forecast errors (α is less than 0.5), while in the quadratic specification, we find that positive forecast errors are more costly (α is greater than 0.5). Under either specification we find that GS analysts tend to have a lower α, which can be interpreted as stronger incentives to issue lower forecasts. Finally, under either specification we document a downward trend in α.

Our results are robust to using alternative definitions of consensus forecast and alternative deflator variables. In particular, the results do not change when we use the mean of individual analyst forecasts as a measure of consensus or when we scale all variables by price at time t-1 rather than t-2, or by total assets at time t-2. Excluding observations for which price is less than $1 had no effect on our findings.

We conducted the same analysis for forecasts issued in the second half of the quarter. We find that the cost of positive forecast errors is even lower, and that some, but not all, findings of inefficient information use disappears. Overall, we are still able to document two distinct phenomena.

5. Conclusions

Financial analysts' consensus earnings forecast errors have been extensively studied from two diametric perspectives. The first one emphasizes the effect of incentives but pays little attention to the issue of how well analysts use information in responding to these incentives. The second one focuses on how analysts use information with little attention to the effect of incentives on forecast errors. Adopting one of two perspectives is unnecessary, and limits our understanding of financial analysts' forecasting behavior because both incentives and cognitive biases are likely to simultaneously affect the properties of analysts' forecast errors.

The most distinctive feature of our empirical analysis of quarterly earnings forecast errors is that it combines the two perspectives.[11] We are able to simultaneously document that analysts' incentives are asymmetric and that analysts do not use information efficiently in minimizing their expected loss. In the linear specification, we find that positive forecast errors are less costly than positive forecast errors ($\alpha<0.5$). This finding is reversed in the quadratic specification in which we document a higher cost of positive forecast errors ($\alpha>0.5$). The reversal in asymmetry suggests that the choice of specification matters for our inferences about analysts' incentives and that more research on how accuracy is measured and rewarded is needed.

We also examine whether analysts' incentives and use of information vary across brokerages and over time. We find no evidence to support the argument that analysts employed by firms that participated in the Global Settlement of 2003 issued more biased research as a result of investment-banking considerations. It is possible, however, that our tests have low

[11] In other words, we view the forecast as a choice that analysts make in trying to enhance their welfare--a departure from the literature's tradition of viewing forecasts as exogenously given (Demski, 2004). In a survey of the use of expectations in accounting research, Demski forcefully argues that reliance on exogenous expectations structures limits the depth and boundaries of teaching and research (p. 519).

power. Perhaps, differences in incentives are more likely to manifest themselves in annual earnings and recommendations (Kadan et al., 2004). A natural extension of our analysis would be to examine the loss function implicit in analysts' long-term annual and quarterly earnings forecasts.

We find that over time the cost of making positive forecast errors (α) goes down, and that analysts appear to use information more efficiently. Due to competitive and regulatory pressures, the market of investment research seems to have evolved toward greater information efficiency. Whether users benefit from the decrease (increase) in the cost of positive (negative) errors is unclear since under the linear loss function, the decrease in the cost of positive forecast errors means even greater loss function asymmetry.

In this study, we consider only a few information variables suggested by prior research as being inefficiently used by financial analysts. The econometric approach of separating the effects of incentives from the effects of inefficient use of information can be applied to other information variables such as extreme past earnings (Easterwood and Nutt, 1999), accruals (Bradshaw et al., 2001), and past returns (Lys and Sohn, 1990). Another potential venue for future research would be to conduct a similar analysis of individual analysts' earnings forecasts. Understanding the forecasting behavior of individual analysts is essential for understanding how the market for investment research functions.

References

Abarbanell, J. S., and R. Lehavy, 2003, Biased forecasts or biased earnings? The role of reported earnings in explaining apparent bias and over/underreaction in analysts' earnings forecasts, *Journal of Accounting and Economics* 36 (1-3), 105-146.

Basu, S., and S. Markov, 2004, Loss function assumptions in rational expectations tests on financial analysts' earnings forecasts, *Journal of Accounting and Economics* 38, 171-203.

Bradley, D., B. Jordan, and J. Ritter, 2004, Analyst behavior following IPOs: the "bubble period" evidence, Working Paper, University of Florida.

Bradshaw, M., S. Richardson, and R. Sloan, 2001, Do analysts and auditors use information in accruals? *Journal of Accounting Research* 39 (1), 45-74.

Chen, Q., and W. Jiang, 2005, Analysts' weighting of private and public information, Forthcoming in *Review of Financial of Studies*.

Cohen, D. A., and T. Z. Lys, 2003, A note on analysts' earnings forecast errors distribution, *Journal of Accounting and Economics* 36 (1-3), 147-164.

Das, S., C.B. Levine and K. Sivaramakrishnan, 1998, Earnings predictability and bias in analysts' earnings forecasts, *The Accounting Review* 73 (2), 277-294.

Demski, J., 2004. Endogenous expectations, *The Accounting Review* 70 (2), 519-539.

Dorfman, J., 1991, Heard on the street: analysts devote more time to selling as firms keep scorecard on performance, *The Wall Street Journal*, October 29, C1.

Dugar, A., and S. Nathan, 1995, The effects of investment banking relationships on financial analysts' earnings forecasts and investment recommendations, *Contemporary Accounting Research* 12 (1), 131-160.

Easterwood, J., and S. Nutt, 1999, Inefficiency in analysts' earnings forecasts: systematic misreaction or systematic optimism? *The Journal of Finance* 54 (5), 1777-1797.

Elliot, G., I. Komunjer, and A. Timmerman, 2004a, Estimation and testing of forecast rationality under flexible loss, Forthcoming in *Review of Economic Studies*.

Elliot, G., I. Komunjer, and A. Timmerman, 2004b, Biases in macroeconomic forecasts: irrationality, or asymmetric loss? Working Paper, University of California at San Diego.

Francis, J., and D. Philbrick, 1993, Analysts' decisions as products of a multi-task environment, *Journal of Accounting Research* 31 (2), 216-230.

Gu, Z., and J. Wu, 2003, Earnings skewness and analyst forecast bias, *Journal of Accounting and*

Economics 35 (1), 5-29.

Hansen, L., and K. Singleton, 1982, Generalized instrumental variables estimation of nonlinear rational expectations models, *Econometrica* 50, 714-735.

Hayes, R. M., 1998, The impact of trading commission incentives on analysts' stock coverage decisions and earnings forecasts, *Journal of Accounting Research* 36 (2), 299-320.

Irvine, P., 2000. Do analysts generate trades for their firms? Evidence from the Toronto stock exchange, *Journal of Accounting and Economics* 30 (2), 209-226.

Kadan, O., R. Wang, and T. Zach, 2004, Are analysts still biased? Evidence from the post 'Global Settlement' period, Working Paper**,** Washington University.

Lambert, R., 2004, Discussion of analysts' treatment of non-recurring items in street earnings and loss function assumptions in rational expectations tests on financial analysts' earnings forecasts, *Journal of Accounting and Economics* 38, 205-222.

Lim, T., 2001, Rationality and analysts' forecast bias, *The Journal of Finance* 56 (1), 36-385.

Lin, H., and M. McNichols, 1998, Underwriting relationships, analysts' earnings forecasts and investment recommendations, *Journal of Accounting and Economics* 25 (1), 101-127.

Lys, T., and S. Sohn, 1990, The association between revisions of financial analysts' earnings forecasts and security-price changes, *Journal of Accounting and Economics* 13 (4), 341-363.

Skiles, M., 2003, After the bubble has burst: new regulations for analysts in the U.S., *SIA Research Reports*, Vol. 4, #5.

Soffer, L., and T. Lys, 1999, Post-Earnings Announcement Drift and the Dissemination of Predictable Information, *Contemporary Accounting Research*, 16 (2) 305-331.

Appendix 1 Sample construction details

		Number of forecasts		
		All firms	**GS firms**	**Non-GS firms**
Number of forecasts		872,857	278,024	594,833
Less:	Outside Pre-Reg FD, Reg FD-GS, and Post-GS periods	(17,181)	(5,665)	(11,516)
		855,676	272,359	583,317
	Not the first available	(84,704)	(27,303)	(57,401)
Remaining number of forecasts		770,972	245,056	525,916
	Number of analysts	10,906	3,349	8,622
	Number of investment firms	605	11	594
Number of consensus forecasts		194,892	108,720	173,194
Less	Missing price, lagged earnings and lagged forecasts	(36,362)	(22,602)	(36,556)
Remaining consensus forecasts		158,530	86,118	136,638
Period 1 (Pre-Reg FD)				
	Remaining consensus forecasts	119,829	65,172	103,131
Period 2 (RegFD-GS)				
	Remaining consensus forecasts	22,776	12,893	19,448
Period 3 (Post-GS)				
	Remaining consensus forecasts	15,925	8,053	14,059

Table 1. Descriptive statistics

A_{t+1} is the quarterly IBES EPS for the quarter $t+1$. F_t^{t+1} is the median consensus EPS forecast of A_{t+1} constructed from forecasts issued in the first half of the interval between the announcement of A_t and A_{t+1}. FE_t^{t+1} is the corresponding forecast error for the quarter $t+1$. $(A_t - A_{t-1})$ is the earnings change in the quarterly IBES EPS for the quarter t. All variables are scaled by share price recorded for the earnings announcement month of quarter t-1 obtained from IBES. Mean, standard deviation, median 1st and 3rd quartiles of the variables are reported. Variables are generated from the median consensus of all available quarterly forecasts (*All firms*), consensus of only global settlement investment firm analysts' quarterly forecasts (*GS firms*) and consensus of all non-settlement investment firm analysts' quarterly forecasts (*non-GS firms*). Within each classification, we also split the data across three different periods: (1) *Pre-Reg FD*: 1985-September 2000; (2) *Reg FD–GS*: October 2000-December 2002; (3) *Post-GS*: April 2003-December 2004. All variables are winsorized at the 1% level on both tails. The sample period is 1985 – 2004. Only observations without missing F_t^{t+1}, FE_t^{t+1}, A_{t+1} and $(A_t - A_{t-1})$ are used in the analysis.

Panel A. Number of analysts employed and companies covered

	Mean	SD	0.25	Median	0.75	Companies covered
Pre-RegFD						
GS firms	64.74	29.52	48.68	64.89	75.73	1701.94
Non-GS firms	6.94	10.23	1.31	3.50	8.00	2581.88
Reg FD-GS[12]						
GS firms	126.90	55.78	108.75	129.00	161.63	2216.00
Non-GS firms	11.92	17.25	2.00	5.00	14.50	3260.00
Post-GS						
GS firms	108.28	18.72	94.50	111.50	116.50	1803.00
Non-GS firms	9.39	14.64	1.50	3.50	11.75	3022.00

[12] Note that the statistics presented in this table do not include the period from Oct 2000 to Dec 2000. The statistics on the calendar year 2000 are included in the period *Pre-RegFD*. For the period *Post-GS*, the year 2003 is included.

Panel B. Number of forecasts included in the consensus forecast and number of companies covered

	Mean	S.D.	0.25	Median	0.75
Pre-Reg FD					
All firms	5.274	4.038	2	4	7
GS firms	2.397	1.410	1	2	3
Non-GS firms	3.938	3.021	2	3	5
Reg FD-GS					
All firms	7.204	5.481	3	6	10
GS firms	3.198	1.866	2	3	4
Non-GS firms	5.146	3.988	2	4	7
Post-GS					
All firms	7.966	6.108	3	6	11
GS firms	3.290	1.903	2	3	4
Non-GS firms	5.925	4.575	3	5	8

Panel C. Descriptive statistics of variables

	All firms consensus					GS firms forecast					Non-GS firms forecast				
	Mean	SD	0.25	Median	0.75	Mean	SD	0.25	Median	0.75	Mean	SD	0.25	Median	0.75
Pre-Reg FD															
F_t^{t+1}	0.0128	0.0199	0.0079	0.0147	0.0218	0.0141	0.0174	0.0090	0.0152	0.0219	0.0130	0.0188	0.0080	0.0147	0.0216
FE_t^{t+1}	-0.0022	0.0141	-0.0020	0.0000	0.0016	-0.0012	0.0110	-0.0013	0.0002	0.0015	-0.0019	0.0124	-0.0019	0.0000	0.0016
A_{t+1}	0.0104	0.0269	0.0065	0.0142	0.0218	0.0127	0.0226	0.0083	0.0149	0.0221	0.0109	0.0248	0.0068	0.0142	0.0216
$(A_t - A_{t-1})$	0.0006	0.0220	-0.0036	0.0006	0.0043	0.0004	0.0185	-0.0030	0.0006	0.0038	0.0005	0.0201	-0.0034	0.0006	0.0041
N=	119,829					65,172					103,131				
Reg FD-GS															
F_t^{t+1}	0.0029	0.0282	-0.0020	0.0087	0.0178	0.0037	0.0251	0.0000	0.0085	0.0165	0.0042	0.0256	-0.0006	0.0089	0.0179
FE_t^{t+1}	-0.0011	0.0135	-0.0009	0.0003	0.0018	-0.0002	0.0103	-0.0003	0.0003	0.0016	-0.0009	0.0118	-0.0007	0.0003	0.0017
A_{t+1}	0.0013	0.0344	-0.0034	0.0086	0.0180	0.0030	0.0296	-0.0007	0.0086	0.0169	0.0028	0.0308	-0.0019	0.0088	0.0181
$(A_t - A_{t-1})$	0.0009	0.0220	-0.0034	0.0004	0.0037	0.0006	0.0189	-0.0031	0.0004	0.0032	0.0005	0.0194	-0.0032	0.0004	0.0034
N=	22,776					12,893					19,448				
Post-GS															
F_t^{t+1}	0.0068	0.0259	0.0036	0.0118	0.0186	0.0085	0.0229	0.0052	0.0120	0.0187	0.0070	0.0244	0.0038	0.0118	0.0183
FE_t^{t+1}	-0.0007	0.0136	-0.0006	0.0005	0.0024	-0.0002	0.0112	-0.0002	0.0006	0.0021	-0.0004	0.0121	-0.0005	0.0005	0.0023
A_{t+1}	0.0059	0.0315	0.0038	0.0123	0.0193	0.0083	0.0266	0.0055	0.0125	0.0195	0.0063	0.0290	0.0040	0.0122	0.0191
$(A_t - A_{t-1})$	0.0016	0.0221	-0.0028	0.0006	0.0046	0.0010	0.0188	-0.0025	0.0006	0.0039	0.0014	0.0200	-0.0027	0.0006	0.0044
N=	15,925					8,053					14,059				

Table 2. Estimation of alphas and J-statistics using a linear loss function

We estimate α from the FOC: $E\left[V_t \cdot \left(1\left(FE^*_{t+1} < 0\right) - \alpha\right) \cdot \left|FE^*_{t+1}\right|^0\right] = 0$ using the two-step efficient Generalized Method of Moments (GMM). V_t is a vector of instrument, and FE is the forecast error, as defined in Table 1. α=0.5 represents the case of loss function symmetry. α>0.5 represents the case of analysts' incentives to issue optimistic forecasts. α<0.5 represents the case of analysts' incentives to issue pessimistic forecasts. The reported Hansen's J-statistic[13] measures how close to optimality the forecasts are (Elliott et al., 2004a, b). It has a chi-square distribution with degrees of freedom equal to the difference between the number of moments and number of parameter estimated. Large values of the J-statistic result in a rejection of the null hypothesis of forecast optimality. We report α and J-statistics for All firms, GS firms, and Non-GS firms over three time periods: (1) *Pre-Reg FD*: 1985-September 2000; (2) *Reg FD–GS***:** October 2000-December 2002; (3) *Post-GS***:** April 2003-December 2004.. In parentheses are robust standard errors for α and p-value for J-statistics. We allow for heteroscedasticity and intra-quarter correlation. The last column reports the difference in α between GS firms and Non-GS firms. The reported p-value, in parenthesis, is from the test of the hypothesis that the difference is zero. The test statistic is calculated as $(\alpha_{Non-GS} - \alpha_{GS})^2 / [\text{var}(\alpha_{Non-GS}) + \text{var}(\alpha_{GS})]$. It follows a χ^2 distribution with degrees of freedom 1. α's not significantly different from 0.5 at the 1% level are in bold.

Panel A: Pre-Reg FD period

All Firms		GS Firms		Non-GS Firms		
alpha	**J-stat**	**alpha**	**J-stat**	**alpha**	**J-stat**	$\alpha_{Non-GS} - \alpha_{GS}$
Instruments : Constant only						
0.411		0.385		0.412		0.027
(0.012)		(0.013)		(0.012)		(0.130)
Instruments: Past forecast error and constant						
0.428	53.212	0.418	31.199	0.443	34.196	0.025
(0.012)	(0.000)	(0.012)	(0.000)	(0.011)	(0.000)	(0.122)
Instruments: Past earnings change and constant						
0.422	35.569	0.388	27.411	0.426	37.337	0.038
(0.012)	(0.000)	(0.013)	(0.000)	(0.012)	(0.000)	(0.035)
Instruments: Past earnings at lags 1and 2, past forecast error at lag 1 and constant						
0.425	52.956	0.404	44.478	0.437	45.209	0.033
(0.011)	(0.000)	(0.011)	(0.000)	(0.011)	(0.000)	(0.031)

[13] The Hansen's J-statistic is equal to the minimized value of $J = Ng_t(\alpha)' Sg_t(\alpha)$, where N is the sample size, $g_t(\alpha)$ is the first order condition, $E[V_t(FE_{t+1}<0) - \alpha)|FE_{t+1}|^{p-1}] = 0$, and S is the optimal weighting matrix (see Section 2.3). In STATA we use **ivreg2** with the **gmm** option which utilizes the two-step efficient GMM, and the optimal weighting matrix is the inverse of the covariance matrix of orthogonality conditions. Note that there should be at least two instruments to be able to estimate this statistic.

Panel B: **Reg FD-GS period**

All Firms		GS Firms		Non-GS Firms		
alpha	**J-stat**	**alpha**	**J-stat**	**alpha**	**J-stat**	$\alpha_{Non-GS} - \alpha_{GS}$
Instruments : Constant only						
0.325		0.284		0.321		0.037
(0.015)		(0.011)		(0.014)		(0.031)
Instruments: Past forecast error and constant						
0.318	9.070	0.284	7.545	0.328	8.744	0.044
(0.015)	(0.003)	(0.011)	(0.006)	(0.014)	(0.003)	(0.012)
Instruments: Past earnings change and constant						
0.313	6.822	0.283	4.163	0.306	7.395	0.023
(0.014)	(0.009)	(0.011)	(0.041)	(0.013)	(0.007)	(0.165)
Instruments: Past earnings at lags 1and 2, past forecast error at lag 1 and constant						
0.323	9.394	0.289	7.706	0.321	9.440	0.032
(0.010)	(0.024)	(0.009)	(0.053)	(0.007)	(0.024)	(0.004)

Panel C: **Post-GS period**

All Firms		GS Firms		Non-GS Firms		
alpha	**J-stat**	**alpha**	**J-stat**	**alpha**	**J-stat**	$\alpha_{Non-GS} - \alpha_{GS}$
Instruments : Constant only						
0.298		0.265		0.293		0.028
(0.007)		(0.010)		(0.008)		(0.026)
Instruments: Past forecast error and constant						
0.312	13.452	0.271	8.529	0.306	8.410	0.035
(0.006)	(0.000)	(0.010)	(0.003)	(0.007)	(0.004)	(0.003)
Instruments: Past earnings change and constant						
0.300	1.635	0.269	2.405	0.297	3.153	0.028
(0.007)	(0.201)	(0.010)	(0.121)	(0.008)	(0.076)	(0.022)
Instruments: Past earnings at lags 1and 2, past forecast error at lag 1 and constant						
0.301	22.545	0.267	9.496	0.304	9.675	0.037
(0.005)	(0.000)	(0.005)	(0.023)	(0.006)	(0.022)	(0.000)

Table 3. Estimation of alphas and J-statistics using a quadratic loss function

We estimate α from the FOC: $E\left[V_t \cdot \left(1\left(FE^*_{t+1} < 0\right) - \alpha\right) \cdot \left|FE^*_{t+1}\right|^1\right] = 0$ using the two-step efficient Generalized Method of Moments (GMM). V_t is a vector of instrument, and FE is the forecast error, as defined in Table 1. α=0.5 represents the case of loss function symmetry. α>0.5 represents the case of analysts' incentives to issue optimistic forecasts. α<0.5 represents the case of analysts' incentives to issue pessimistic forecasts. The reported Hansen's J-statistic measures how close to optimality the forecasts are (Elliott et al., 2004a, b). It has a chi-square distribution with degrees of freedom equal to the difference between the number of moments and number of parameter estimated. Large values of the J-statistic result in a rejection of the null hypothesis of forecast optimality. We report α and J-statistics for *All firms*, *GS firms*, and *Non-GS firms* over three time periods: (1) *Pre-Reg FD*: 1985-September 2000; (2) *Reg FD–GS***:** October 2000-December 2002; (3) *Post-GS***:** April 2003-December 2004. In parentheses are robust standard errors for α and p-value for J-statistics. We allow for heteroscedasticity and intra-quarter correlation. The last column reports the difference in α between *GS brokers* and *Non-GS brokers*. The reported p-value, in parenthesis, is from the test of the hypothesis that the difference is zero. The test statistic is calculated as $(\alpha_{Non-GS} - \alpha_{GS})^2 / [\mathrm{var}(\alpha_{Non-GS}) + \mathrm{var}(\alpha_{GS})]$. It follows a χ^2 distribution with degrees of freedom 1. α's not significantly different from 0.5 at the 1% level are in bold.

Panel A: Pre-Reg FD period

All Firms		GS Firms		Non-GS Firms		
alpha	J-stat	alpha	J-stat	alpha	J-stat	$\alpha_{Non-GS} - \alpha_{GS}$
Instruments : Constant only						
0.685		0.635		0.674		0.039
(0.010)		(0.013)		(0.010)		(0.013)
Instruments: Past forecast error and constant						
0.778	50.215	0.663	32.556	0.707	35.397	0.043
(0.008)	(0.000)	(0.012)	(0.000)	(0.009)	(0.000)	(0.003)
Instruments: Past earnings change and constant						
0.694	22.667	0.636	15.457	0.686	29.060	0.050
(0.009)	(0.000)	(0.012)	(0.000)	(0.009)	(0.000)	(0.001)
Instruments: Past earnings at lags 1and 2, past forecast error at lag 1 and constant						
0.762	50.650	0.686	45.654	0.720	48.284	0.034
(0.008)	(0.000)	(0.011)	(0.000)	(0.008)	(0.000)	(0.014)

Panel B: **Reg FD-GS period**

All Firms		GS Firms		Non-GS Firms		$\alpha_{Non-GS} - \alpha_{GS}$
alpha	J-stat	alpha	J-stat	alpha	J-stat	
Instruments : Constant only						
0.599		**0.525**		0.591		0.066
(0.021)		(0.023)		(0.019)		(0.025)
Instruments: Past forecast error and constant						
0.686	9.226	0.574	7.577	0.635	7.915	0.060
(0.023)	(0.002)	(0.029)	(0.006)	(0.023)	(0.005)	(0.107)
Instruments: Past earnings change and constant						
0.576	6.131	**0.517**	3.758	0.566	5.777	0.049
(0.019)	(0.013)	(0.022)	(0.053)	(0.016)	(0.016)	(0.070)
Instruments: Past earnings at lags 1and 2, past forecast error at lag 1 and constant						
0.649	9.408	**0.542**	7.477	0.641	8.536	0.099
(0.023)	(0.024)	(0.027)	(0.058)	(0.017)	(0.036)	(0.002)

Panel C: **Post-GS period**

All Firms		GS Firms		Non-GS Firms		$\alpha_{Non-GS} - \alpha_{GS}$
alpha	J-stat	alpha	J-stat	alpha	J-stat	
Instruments : Constant only						
0.557		**0.520**		0.541		0.021
(0.022)		(0.031)		(0.022)		(0.572)
Instruments: Past forecast error and constant						
0.753	11.818	0.626	8.024	0.663	8.998	0.036
(0.027)	(0.001)	(0.042)	(0.005)	(0.018)	(0.003)	(0.421)
Instruments: Past earnings change and constant						
0.576	3.604	**0.527**	1.359	0.570	5.687	0.043
(0.018)	(0.058)	(0.029)	(0.244)	(0.016)	(0.017)	(0.199)
Instruments: Past earnings at lags 1and 2, past forecast error at lag 1 and constant						
0.668	18.007	0.605	9.392	0.648	10.381	0.043
(0.016)	(0.000)	(0.027)	(0.025)	(0.016)	(0.016)	(0.169)